Constitutive relationship modeling and prediction of armor steel using an artificial neural network

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Summary An artificial neural network (ANN) is established to predict plastic behaviors of the 603 armor steel, based on experimental results with strain rates ranging from 0.001 s^{-1} to 4500 s^{-1}, and temperatures from 288 K to 873 K. Both the descriptive and the predictive capabilities of the ANN model are checked, and compared with several phenomenological and physically based constitutive models. The results show that the ANN model may serve as a valid and effective tool to predict plastic behaviors of the 603 steel under complex loading conditions.

INTRODUCTION

In recent years, the artificial neural network (ANN) approach has been introduced into the field of materials science as a powerful mathematical modeling technique and found growing application in materials property determination. This technique is particularly suitable for modeling non-linear problems involving the manipulation of multiple parameters and interpolation. However, the experimental data used to train the networks were usually in restricted temperature and strain rate ranges. Moreover, mechanical properties of materials are predicted mainly under single-step deformation conditions, without consideration of the effect of loading history. In our previous work [1-3], mechanical behaviors of BCC and FCC metals were studied systematically over wide temperature and strain rate ranges. Two phenomenological and five physically based constitutive models have been established to describe and predict the plastic behaviors of the materials. In the present work, a three-layer feed-forward ANN is used to characterize the constitutive relationship of the 603 armor steel at temperatures ranging from 288 K to 873 K, and strain rates ranging from 0.001 s^{-1} to 4500 s^{-1}. Validity of this ANN model is checked by the strain rate jump tests. Descriptive and predictive capabilities of this approach are compared with other constitutive models.

ESTABLISHMENT OF ANN MODEL

The structure of the neural network is schematically shown in Fig. 1. The inputs of the ANN model are plastic strain, log strain rate, and deformation temperature, while the output is flow stress. The design and training of the ANN model is performed using the neural network toolbox of the MATLAB software. The hidden layer uses a hyperbolic tangent sigmoid (tansig) transfer function, and the output layer uses a linear (purelin) transfer function to map the output parameters. In this model, the Levenberg-Maquarolt algorithm is used to train the network for fast optimization. For dynamic tests, the adiabatic temperature rise in the material during plastic deformation is considered. In order to determine an appropriate number of neurons in the hidden layer, a series of ANN models have been developed using the unified datasets, with the hidden layer neurons ranging from 1 to 20. From Fig. 2 it is observed that mean square error (*MSE*) and correlation coefficient (*R*) change abruptly at first with the increase of the hidden layer neurons. However, when more than 4 neurons are used, *MSE* and *R* change at a much lower rate. After the neuron number exceeds 11, the values of both *MSE* and *R* reach a comparatively stable state. Hence 11 neurons are used in the hidden layer of our ANN model, in consideration of both the network performance and the computation cost.

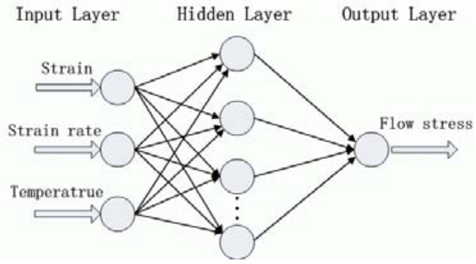

Fig. 1 Schematic structure of the ANN model

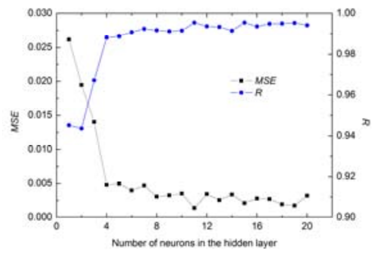

Fig. 2 Network performance variation with neurons in the hidden layer

DISCUSSION

ANN Model performance

The performance of the network at each epoch of training is also checked by *MSE* between experimental data and network output. The best performance is achieved at epoch 38, with *MSE*=0.002859. The corresponding correlation coefficient at this epoch is 0.9941. With the trained ANN model, the description of plastic behavior of the material at

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different loading conditions is presented in Fig. 3. The model prediction can precisely simulate the plastic behaviors of the material at each specific strain rate and temperature level. For dynamic tests, the oscillations of the experimental data are not characterized by this ANN model, which describes the flow stress with comparatively smooth curves.

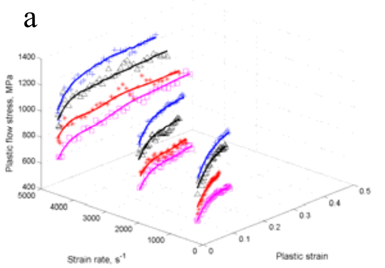

Fig. 3 ANN model description of plastic behavior of the 603 armor steel at different loading conditions: (a) dynamic, and (b) quasi-static (Symbols represent experimental data, with + for 288 K, Δ for 473 K, * for 673 K, and □ for 873 K; solid lines are model description, with the same color as the symbol for each initial temperature.)

Predictive capability

For verification of the predictive capability, the obtained ANN model is used to simulate the strain rate jump tests[1,2] with initial temperature T_0. In the model prediction, isothermal results are firstly obtained by the ANN model for all the three loading steps, then adiabatic temperature rise is calculated in the third loading step. With the newly generated input vectors, the flow stress of the third loading step is predicted again with deformation temperature T. Both the isothermal and the final results are shown in Fig. 4. The ANN model prediction is in good agreement with the experimental results under the condition of 753 K and 0.002 s^{-1}. But for the subsequent loading step, the ANN model overestimates the measured values. In the third loading step, with consideration of adiabatic temperature rise the predictive capability of the ANN model is evidently improved.

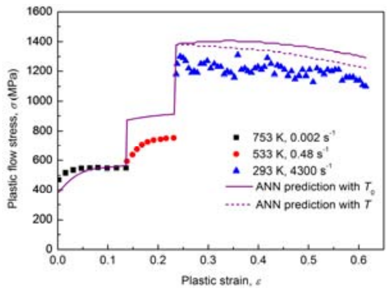

Fig. 4 Comparison between the measured and the predicted flow stress for the strain rate jump tests

The description and prediction errors are shown in Fig. 5, together with the average error of the quasi-static and dynamic tests for each constitutive model. It is interesting to note that in Fig. 5(a), description error of the ANN model is much lower than that of all the other models, for the both loading conditions. Comparison of prediction errors of different models is shown in Fig. 5(b). The average value of the quasi-static and dynamic errors of the ANN model is 11.80%, less than most of the other models. Similar to most of the other models, the ANN model has a larger error for the quasi-static tests than the dynamic tests, due to the comparatively large errors that occur in the prediction of the second loading step. Comparing to the other constitutive models, besides its superior performance in description of the training data and a considerable precision in prediction, the ANN approach is very convenient in model establishment and data processing. Once the input and output datasets are supplied, an ANN model with a predesigned performance goal can be developed automatically by self-training.

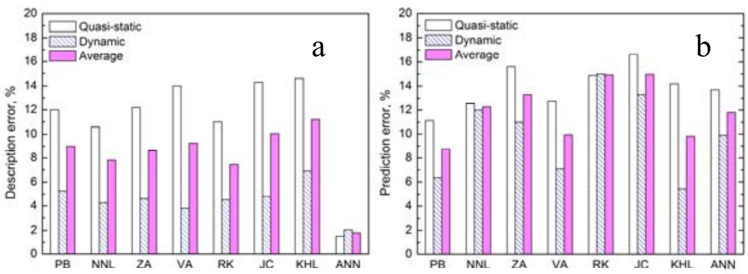

Fig. 5 Comparison of the ANN model performance with other constitutive models: (a) description of the basic experimental data, and (b) prediction of the strain rate jump tests

CONCLUSIONS

The ANN model has a much better flexibility than the other models in characterization of the basic experimental data. Both the temperature and the strain rate effects on the flow stress can be described successfully by this model. The average description error is only 1.78% for both the quasi-static and the dynamic loading conditions. In the prediction of the flow stress in the strain rate jump tests, the ANN model exhibits a better accuracy than most of the other models, with an average error of 11.80%. The results show that the ANN model developed here may serve as a valid and effective tool to characterize plastic behaviors of the 603 steel under complex loading conditions.

References

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